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The use of pedo-transfer functions for estimating soil organic carbon contents in maize cropland ecosystem in the Coastal Plains of Tanzania

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ABSTRACT

Soil organic carbon (OC) plays a vital role on physico-chemical and biological properties of soils and on climate change regulation. The use of pedo-transfer functions from easily available soil properties for estimating soil OC could be fast and cheap when considering field and laboratory work implications especially in Sub Saharan Africa including Tanzania. This paper attempts to develop a model for estimating soil OC contents under maize croplands ecosystem using pedo-transfer functions from soil texture. A total of 100 epipedon data entries were randomly collected from the previous soil sampling works that were conducted under maize croplands in coastal plains of Tanzania. Eighty percent of the collected data were used for training the model by using multiple regression analysis while the remained 20% were used to validate the model. The results indicated that, clay and silt had significant ($p < 0.001$) positive correlation with soil OC while sand contents in soils had negative ($p < 0.001$) correlation with soil OC. All together clay, sand and silt were revealed powerful predictors ($p < 0.001$, $R^2 = 0.82$) of OC content in soils. On validation, the soil OC predicted agreed by 81.2% with the soil OC determined by laboratory test. These results imply that pedo-transfer functions for predicting soil OC based on soil texture is not only fast and cheap but also is an effective option for estimating OC content in soils.

1. Introduction

The soil organic carbon (OC) is the most prevalent form of C in soil and is derived from dead plant materials and remains of dead micro-organisms and animals (Lal, 2012). Soils are the biggest reservoir of organic carbon when excess atmospheric CO_2 is sequestered in soils and transferred to soil OC they thus play a big role on reducing global warming and climate change regulation (Woollen et al., 2012). The CO_2 is a greenhouse gas that traps heat in the atmosphere (Smith et al., 2010). Without CO_2 and other greenhouse gases such as nitrous oxide and methane, the earth would be a frozen planet (IPCC, 2007). However, excess CO_2 in the atmosphere leads to climate change (Woollen et al., 2012). Plants including maize use CO_2, sunlight energy and water to make their own food for their growth (IPCC, 2007). The carbon then becomes part of the plants. When the plants die, the C compounds eventually are transferred, decomposed and incorporated into the soil as soil OC. Thus, plants are the vehicle by which CO_2 is transferred from the atmosphere to soil C. It would be of interest to be able to keep more of that fixed C in the soil environment and to reduce re-emissions back to the atmosphere, where it would increase the CO_2 levels over and above normal levels, thus creating instability or change of climate (Hoffmann et al., 2014). On the other hand the content of OC in soils has direct implications to the soil physico-chemical and biological properties and thus to soil fertility for plant health (IPCC, 2007). A soil with relatively high content of soil OC has relatively higher soil fertility and tends to improve soil physical properties (Hoffmann et al., 2014). While this fact continues to be the case, a different dimension i.e. the climate change regulation dimension of soil OC has of recent come into focus. Because of the above considerations of the implications of soil OC on soil properties, and the potential for climate change regulation when sequestered in soils, there is need for estimating the contents of the OC in our soils and crop land ecosystems.

The OC content in soils varies across tropical landscapes due to a complex mix of climatic, vegetation and edaphic variables (Willcock et al., 2014). In Tanzania and coastal plains in particular, maize is the main cultivated food crop (Mwango et al., 2015a). Thus, estimating soil OC contents in maize cropland ecosystem is essential for monitoring soil health and crop yield but also for climate change regulation. These benefits of soil OC have increased the interest in quantifying the OC contents of soils at farm, regional as well as global level (Jandl et al.,

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2014). However, measuring soil OC contents especially for large tracts of land is costly when considering field and laboratory work that are involved (Jha et al., 2014; Nocita et al., 2014; Shelukindo et al., 2014a). An indirect estimation of soil properties from more easily measurable and more readily available soil properties such as particle size distribution, bulk density and soil pH are referred to as pedo-transfer functions. Studies by Minasny (2007); Bouma (1989) pointed out that the most less laborious, cheap and readily available data are such as field morphology, soil texture, structure and pH. The information on soil texture for example are said to be readily available because the data can be obtained not only from soil surveys but also from many agricultural studies, studies related to irrigation, soil moisture, hydrology and civil works. Pedo-transfer functions add value to this basic information by translating them into estimates of other more laborious and expensively determined soil properties such as soil OC. In recent years, the development of prediction methods that use pedo-transfer functions to spatially extend sparse and expensive soil measurements have been a sharpening focus of research (Keshavarzi et al., 2015).

Worldwide, the prediction of various soil properties has been possible by the use of pedo-transfer functions. Such studies include that of MacDonald (1998) developed two pedo-transfer functions to predict cation exchange capacity (CEC) based on soil organic carbon (OC) and clay (Cl) as CEC = 2.0 OC + 0.5 Cl and CEC = 3.8 OC + 0.5 Cl for Quebec and Alberta soils in Canada, respectively. Al-Busaidi and Cookson (2003) suggested a pedo-transfer function to predict soil sodium adsorption ratio (SAR) based on soil electrical conductivity (EC) as SAR = 0.464 EC + 7.077 with R^2 = 0.83 for saline soils in Oman. Seilsepour et al. (2008) in Iran developed a pedo-transfer function for estimating available soil phosphorus (AP) using soil OC as AP = 0.7927 $e^{4.9922OC}$ with R^2 = 0.92. A study by Rashidi and Seilsepour (2008) in Iran developed a pedo-transfer function to predict soil CEC based on soil organic carbon and pH as CEC = 26.76 + 8.06 OC – 2.45 pH with R^2 = 0.77. In Iran, Seilsepour and Rashidi (2008) also predicted soil CEC from organic carbon using a pedo-transfer function as CEC = 7.93 + 8.72 OC with R^2 = 0.74. Shelukindo et al. (2014b) in Tanzania developed a pedo-transfer function to predict soil organic carbon using total Nitrogen (TN) and Calcium as OC = 0.17 + 17.95TN − 0.29Ca with R^2 = 0.99. So far many pedo-transfer function studies including those of Cosby et al. (1984), Saxton et al. (1986), Wösten and van Genuchten (1988), Vareecken et al. (1989), Jabro (1992), Tietje and Hennings (1996) and Rasoulzadeh (2011) have been conducted for predicting hydraulic conductivity using soil texture, organic carbon and bulk density.

Pedo-transfer studies which involve the more easily measurable and readily available soil properties such as soil texture are frequently been used to predict soil moisture characteristics. Similarly soil texture could also have strong predictive potential on the status of soil properties including OC in soils. However, such pedo-transfer function studies involving particle size distribution for estimating OC contents in soils are limited and not fully understood. The current study was carried out to develop a multiple regression model for estimating soil OC contents using soil texture in maize croplands of the coastal plains ecosystem in Tanzania.

2. Materials and methods

2.1. Study area

A review was conducted in coastal plains of Tanzania covering 4 districts of Tanga and Coat regions namely Mkinga, Pangani, Bagamoyo and Kibaha districts (Fig. 1). The sampling points and salient features of the area under study are presented respectively in Fig. 2 and Table 1. The coastal plains are characterized by an area of flat, low-lying land adjacent to a seacoast and separated from the interior by other features, the plains are low altitude areas below 750 m developed on mainly marine, secondary and tertiary sediments including unconsolidated marine sediments, strongly weathered terrestrial sediments of the Karoo age, sandstone, limestone, dolomites, and gneisses of various mineral compositions (De Pauw, 1984). According to SOTER database for Tanzania as per Eschweiler, 1998, the soil coastal plains are occupied by various soils types, the major soils in the area include *Ferralic Cambisols* and *Rhodic Cambisols* which cover an area of about 4879 sq. km (66.0%), %), *Hypoluvic Arenosols* occupy 792 sq. km (11.0%), *Humi-Gleyic Fluvisols* occupy 282 sq. km (5.2%), *Chromi-Natric Vertisols* occupy 916 sq. km (12.5%) and *Calci-Hyposodic Planosols* which cover 389 sq. km (5.3%) (Hertemink and Bridges, 1995; Eschweiler, 1998).

The coastal plains of Tanzania are geographical areas exhibiting relatively similar climatic conditions. The area experience two rainy seasons with a yearly mean of 1200 mm, and is hot all year round, with a slightly hotter and wetter period from November to April, when daytime temperatures are around 30/31 °C, but with peaks of 32/34 °C, and relative humidity is high, especially in March and April, the rainiest months (De Pauw, 1984; Kanyeka et al., 2007).

The annual precipitation amounts to 1200 mm, with a maximum from March to May; April is the rainiest month receiving about 255 mm, and a secondary maximum, that of the short rains, from October to December. However, the rainfall pattern is quite irregular, so that in some years, the latter period can be very rainy as well. From June to September there is little rain; this period, in addition to being the driest, is also the coolest, with highs around 30/31 °C, and lows around 18 °C, though sometimes at night the temperature can drop to around 15 °C. The amount of sunshine in the study area is good throughout the year, except maybe in April, the wettest month.

2.2. Data collection

The soils data used in this study relied solely on the available legacy information from previous works. Top soil data from natural horizons under soil types namely *Cambisols*, *Arenosols* and *Fluvisols* were collected from the previous soil surveys that were conducted from 2010 to 2015 in smallholder maize farms in the area. This time span was chosen because it was the period when soil sampling work was conducted in the studied area. A total of 100 epipedon data entries were randomly collected from previous works that were conducted under maize croplands. Eighty percent of the collected data were used for training the model while the remained 20% were used to validate the model.

2.3. Statistical analysis

Anderson Darling test was performed to test data normality, while correlation of variables were examined by Spearman rho test under Minitab software. Analysis of variance (ANOVA) was conducted to compare the contents of soil OC, sand, silt and clay under the studied soil types. ANOVA was performed using Statistix.10 analysis software. The soil OC and particle size distribution data points were randomized by using Excel software where 80% of the data was selected to train the model and remaining 20% was used to test the developed model. The collected data on soil OC, sand, silt and clay were further subjected to regression analyses in Minitab software to develop pedo-transfer function models. Regression models are powerful tools frequently used to predict a dependent variable from a set of predictors (Rashidi and Seilsepour, 2008; Shelukindo et al., 2014b; Mwango et al., 2014). They are widely used in a number of different contexts (Minasny, 2007; Seilsepour et al., 2008). The model performance was evaluated using test data points that were not used in the regression training. The test data points were also used to predict soil OC and predicted values were plotted against measured values in a scatter plot. The coefficient of determination (R^2) and the probability levels (p) were used for evaluation of the model. Both linear and multiple regression models were used in this study. Linear regression has the limitation that it handles one dependent variable at a time. A combination of variables cannot be factored into the model. Therefore, multiple regression analysis was

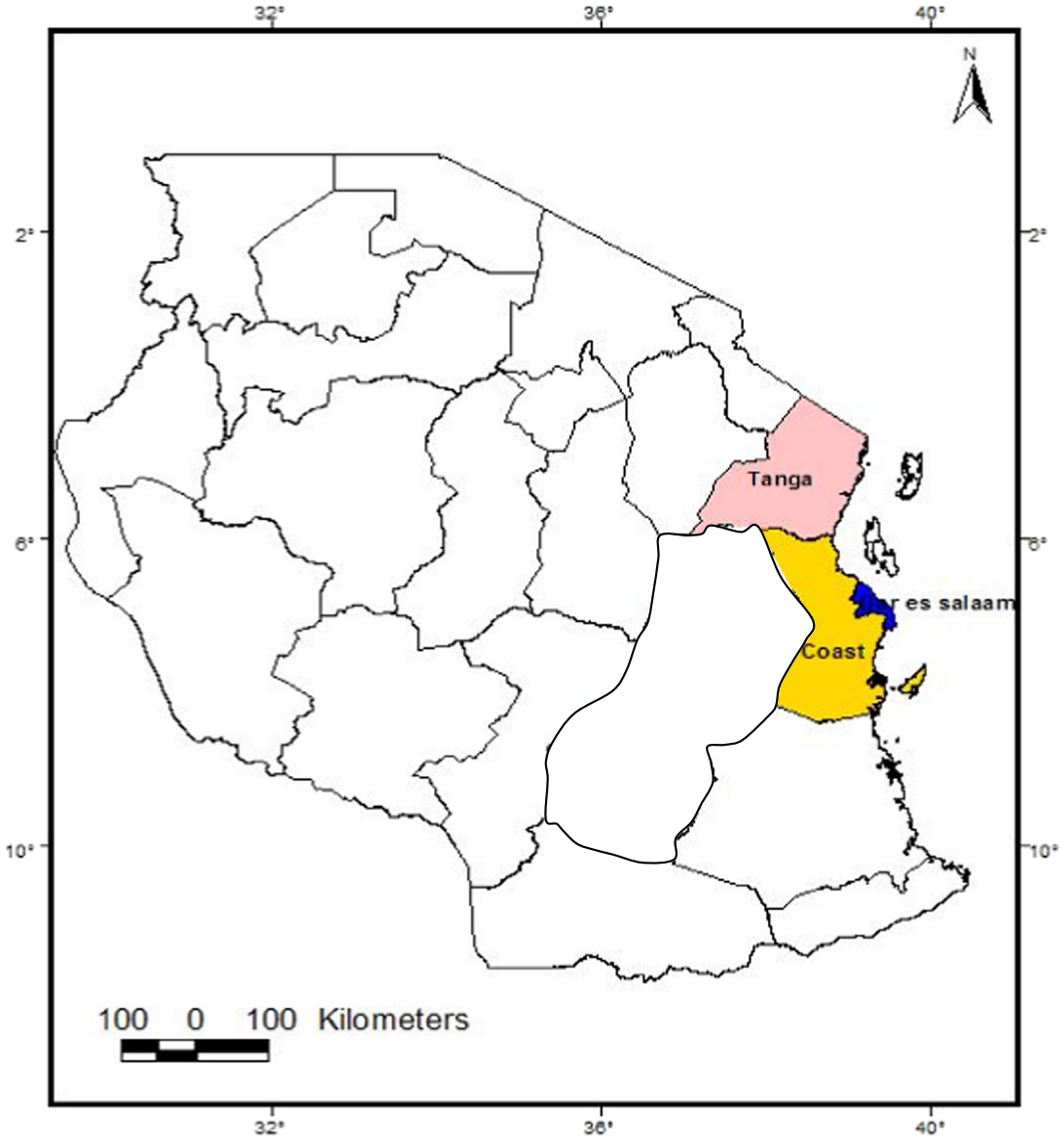

Fig. 1. Location map of the study area.

also undertaken to evaluate the contribution of combined textural particle sizes of the studied soils.

The linear regression model used was: Yi = β0 + β1Xi + €, for i = 1, 2… n. The model is valid for all n pairs of observations (X1, Y1), (X2, Y2)…….. (Xn, Yn); where: Yi = Predicted soil OC content of a soil (dependent variable); Xi = Predictor variable (Independent variable), i.e. soil texture (particle size distribution); β0: = Intercept (a constant) for the relationships between X and Y; β1 = Regression coefficients of the variable that influence soil OC contents in the relationships between X and Y; € is the noise or error associated with the soil OC values.

Multiple linear regressions were used to describe the effects of various independent variables on soil OC contents as the dependent variable. The model employed was: Yn = a + b1 X1 + b2 X2 + …bn Xn + €; where: Yn = Predicted soil OC content of a soil (dependent variable). X1, X2, Xn = Variables which influence soil OC contents (independent variables), i.e. sand, silt and clay; a = Intercept (a constant) for the relationships between X and Y; b1, b2, ….bn = Coefficients of the variables that influence soil OC contents in the relationships between X and Y; € is the noise or error associated with the soil OC values.

3. Results and discussion

3.1. The variations of the soil organic carbon and particle size distribution in the study area

Table 2 presents comparative statistics indicating the influence of soil types on the variability of particle size distribution and contents of soil OC in the study area. It was found that particle size distribution differed significantly ($p < 0.001$) between the studied soil types. While sand contents had the order *Arenosols* > *Cambisols* > *Fluvisols*, clay and silt contents followed the opposite order *Fluvisols* > *Cambisol* > *Arenosols*. Similarly the contents of soil OC differed significantly ($p < 0.001$) between the studied soil types and had the following order *Fluvisols* > *Cambisols* > *Arenosols*. These observations suggest that under similar ecosystem soil texture could be a strong determining factor contributing to OC contents variability in soils. Tables 2 & 3 present the results for the descriptive statistics of the soil particle size and soil OC values used for training and testing the model. All the data on soil OC, sand, silt and clay contents were tested normally distributed ($p < 0.005$) thus were not transformed. The relatively wide range of variations was observed within the studied soil variables as indicated

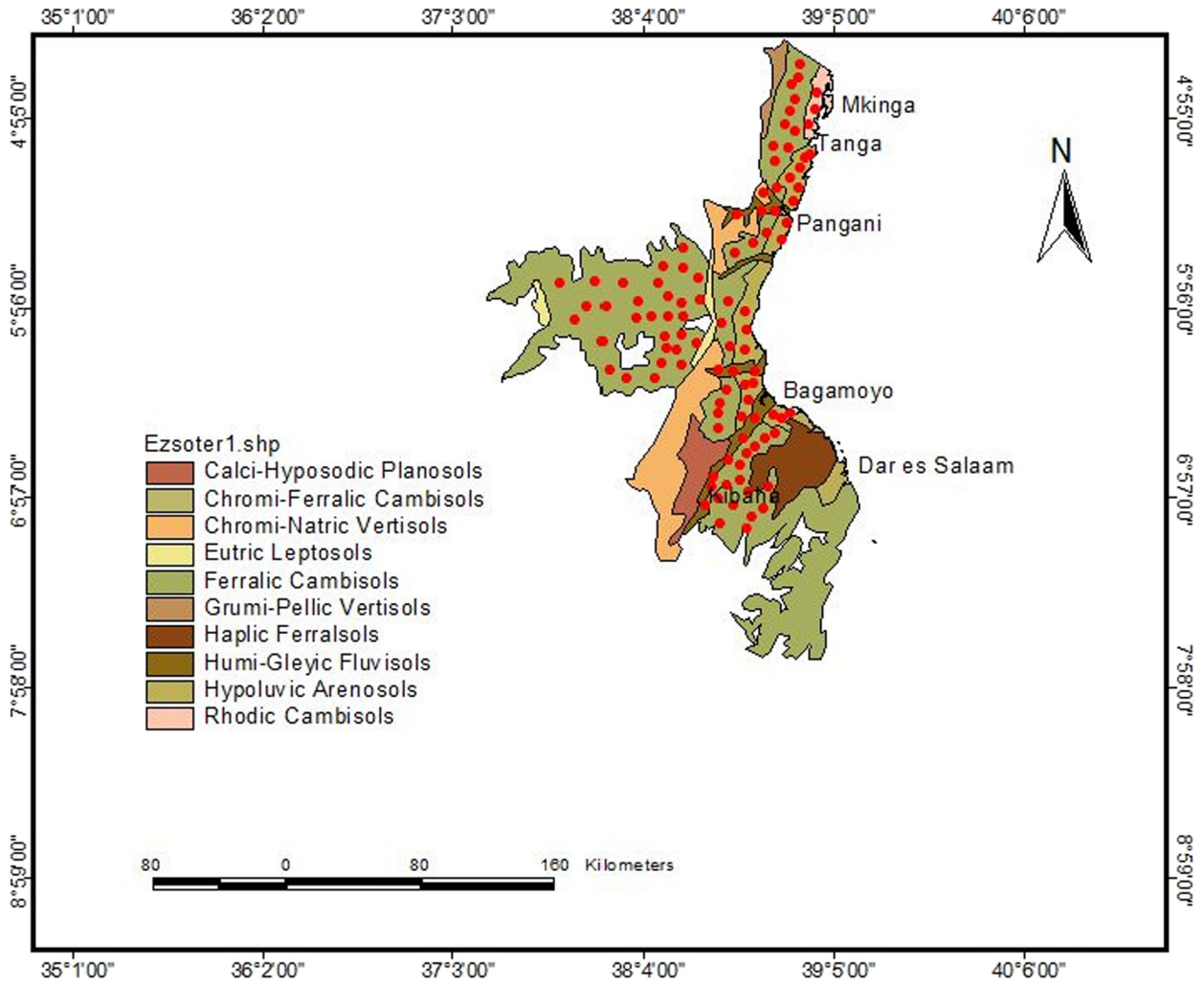

Fig. 2. Sampling points and their respective soil types of the study areas.

by their high standard deviation (StDev) values (Tables 3 & 4). The observed spatial variations of soil OC and soil texture could be explained by the differences in soil types and the terrain topography across the studied area. It is well known that the soil OC content across a landscape are very variable and are influenced by topographical features, vegetation types, climate, soil types, and parent material (Fantappiè et al., 2011).

But this study was conducted on maize farmland of the coastal plains which had similar ecological settings with regards to soil parent materials, climate and vegetation types. Therefore, the overall quantities of soil OC content of the study ecosystem depended merely on the influencing factors due to soil types, and micro topography. According to Mbogoni and Masuki (2001) the physiography of the coastal plains of Tanzania vary from undulating to flatlands and floodplains the variation that could cause a significant differences in the status of soil properties including OC and soil texture in the area. Similar observations were also reported by Mwango (2000) and Meliyo et al. (2014) where soil properties including clay, silt, and OC were revealed higher in valleys than on slopes and summits. According to SOTER database for Tanzania (Eschweiler, 1998) and a study by De Pauw (1984) showed that the coastal plains of Tanzania occupied by soil types mainly *Cambisols*, *Arenosols, Vertisols, Planosols and Fluvisols*. As it has been mentioned earlier that different soil types have different status in soil properties including soil OC and soil texture (FAO, 2014). *Luvisols* for example have higher inborn contents of OC and clay than it does a *Cambisols* or *Arenosols* (FAO, 2014). Studies by Price et al. (2012) and Shelukindo et al. (2014c) revealed that soil OC concentrations in various soils varied in the following order: *Histosols* > *Fluvisols* > *Luvisols* > *Acrisols* > *Cambisols* > *Arenosols*. These observations cement the findings in the current study.

Table 1
Salient features of the study area.[a]

District	AEZ	Altitude (m a.s.l)	Rainfall (mm/year)	Temperature (°C)	Topography	Soil type
Pangani	Coastal plains	265–170	900–1400	19–32	Flat to undulating	*Arenosols* and *Cambisols*
Mkinga	Coastal plains	160–166	900–1400	19–32	Flat to gently undulating	*Arenosols* and *Cambisols*
Bagamoyo	Coastal plains	142–150	900–1200	19–32	Flat to gently undulating	*Arenosols*, *Fluvisols* and *Vertisols*
Kibaha	Coastal plains	153–169	900–1200	19–32	Flat to gently undulating	*Cambisols*

[a] AEZ = Agro-ecological zones; a.s.l = above sea level.

Table 2
The influence of soil types on particle size distribution and contents of soil OC in the study area.

Soil type/Soil texture		Sand %	Silt %	Clay %	OC %
Cambisol	n	64	64	64	64
	Min.	45	4	12.0	0.23
	Max.	78.0	20.0	38.0	1.53
	Mean	58.9	10.8	30.1	0.9
	StDev.	8.1	3.0	6.8	0.5
Arenosol	n	22	22	22	22
	Min.	76.0	2.0	5.0	0.13
	Max.	92.0	10.0	18.0	0.69
	Mean	82.9	6.3	10.8	0.4
	StDev.	3.4	2.2	2.5	0.12
Fluvisol	n	14	14	14	14
	Min.	22.0	8.0	28	1.3
	Max.	60.0	36.0	54	4.2
	Mean	40.0	17.4	40.5	2.1
	StDev.	10.4	8.0	8.1	0.8
P values		< 0.001	< 0.001	< 0.001	< 0.001

Table 3
Descriptive statistics of the studied soil parameters used to develop the model.

Parameter	n	Minimum	Maximum	Mean	StDev
Sand %	80	22	92	69.9	16.7
Silt %	80	2	36	10.3	6.4
Clay %	80	6	46	19.5	11.1
Organic carbon %	80	0.13	4.24	0.87	0.8

Table 4
Descriptive statistics of the studied soil parameters used to validate the model.

Parameter	n	Minimum	Maximum	Mean	StDev
Sand %	20	28	88	46.1	16.6
Silt %	20	2	18	12.1	3.9
Clay %	20	8	54	40.4	14.4
Organic carbon %	20	0.42	2.55	1.38	0.5

3.2. Correlations between soil OC contents and particle size distribution in the study area

The results of the Spearman rho correlation matrix (Table 5) showed significant ($p < 0.001$) correlation between soil OC and particle size distribution of soils. Soil OC had significant positive correlation ($p < 0.001$) with clay and silt, while negatively correlated ($p < 0.001$) with sand contents. Clay contents in the soil had significant positive correlation ($p < 0.001$) with silt but they both negatively correlated ($p < 0.001$) with sand contents. These observations can be explained by the influence of landform where the contents of soil OC, clay and silt are always higher in valleys than on slopes and summits (Shelukindo et al., 2014a). The higher soil OC, clay and silt contents in valleys could be due to the influence of surface runoff that carry with it clay and silt particles together with OC down the slope in valley bottoms (Mwango et al., 2015a). Furthermore, studies by Yao et al. (2010) and Rojas et al. (2012) indicated that soils with high clay contents have high potential to sequester OC than sandy soils. The higher OC contents in clayey soils than in sandy soils is partly due to the fact that sandy soils are more prone to leaching than clayey soils resulting into loosing much of their nutrients including OC on top soils (Hiederer and Köchyl, 2012). But also clays provide both physical and chemical mechanisms to protect or shield soil OC from microbial decomposition (Shelukindo et al., 2014b). Thus the soil OC can be trapped or occluded in the very small spaces between clay particles, making the carbon physically inaccessible to micro-organisms and therefore slowing down its decomposition (Yao et al., 2010; Shelukindo et al., 2014c). In addition, clay provides chemical protection to soil organic matter decomposition through adsorption of soil organic matter onto its surfaces, which again retards soil organic matter decomposition by microbes (Yao et al., 2010; Shelukindo et al., 2014c). Futhermore, the higher moisture storage capacity of the clayey than sandy soils is also a contributing factor to the high soil OC content in clayey soils (Yao et al., 2010; Rojas et al., 2012). Therefore, different soil types differ in their soil OC stocks due to variations in their physico-chemical properties, especially texture and soil moisture (Shelukindo et al., 2014a).

Table 5
Spearman rho correlation matrix between soil OC and soil particle size distribution.

Variables	Constants	% OC	% Clay	% Silt
% Clay	Spearman rho	0.885		
	p value	0.000		
% Silt	Spearman rho	0.648	0.657	
	p value	0.000	0.000	
% Sand	Spearman rho	−0.876	−0.955	−0.821
	p value	0.000	0.000	0.000

3.3. Soil particle size and their potentials for predicting organic carbon contents in soils

The regression models for estimating soil OC contents based on soil texture are shown in Table 6.

It is clear from Table 6 that clay ($R^2 = 0.78$) and silt ($R^2 = 0.57$) contents in soils had positive influence at ($p < 0.001$) on the magnitude of OC content in soils, whereas sand contents in soils had negative influence at ($R^2 = 0.82$, $p < 0.001$). When predictor variables subjected to multiple regression all combinations showed powerful prediction potentials and could significantly ($p < 0.001$) explain about 82% of the variations of soil OC contents in soils (Table 6). Previously, a similar study by Shelukindo et al. (2014b) could predict 99.9% of soil OC using total Nitrogen and Calcium predictor variables. The prediction of soil OC studies by the use of neural network model conducted by Shahri et al. (2011) and Lakzian et al. (2013) could justify 80% and 56% of soil OC, respectively, based on digital elevation model derived parameters. It can be seen that the power of soil texture to predict soil OC contents is lower than it does total Nitrogen in the study by Shelukindo et al. (2014b), this could probably due to the fact that both soil OC and total Nitrogen are derivatives of organic matter upon decomposition thus total Nitrogen is expected to have very strong correlation with OC than it does soil texture. This observation is strongly supported by Xu et al. (2014) and Mwango et al. (2015b) where respectively fields with grass cover and plant leaves mulching was revealed to influence soil properties including soil organic matter, OC and total Nitrogen than fields without grass cover and plant leaves mulching.

Table 6
Regression models for estimating soil OC developed from sand, silt and clay contents.

Regression models	n	R^2	p value
% OC = −0.138 + 0.09771% silt	80	57.3	0.0001
% OC = −0.4029 + 0.06525% clay	80	78.4	0.0001
% OC = 3.986–0.04457% sand	80	81.9	0.0001
% OC = −0.4875 + 0.05153% clay + 0.03402% silt	80	81.8	0.0001
% OC = 4.320–0.0100% silt − 0.04786% sand	80	82.1	0.0001
% OC = 3.088 + 0.0139% clay − 0.03561% sand	80	82.2	0.0001
% OC = 2.57 + 0.0191% clay + 0.0054% silt − 0.0305% sand	80	82.2	0.0001

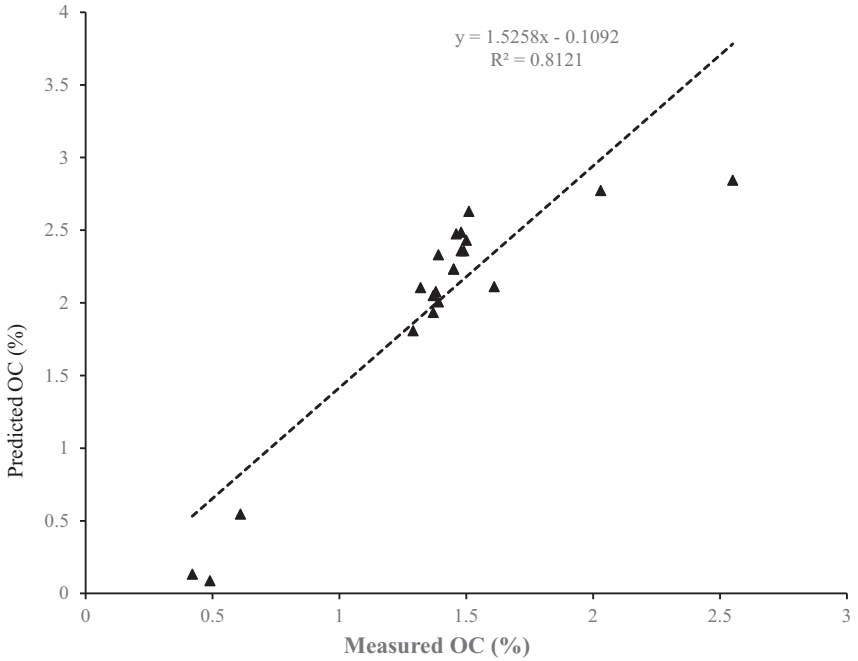

Fig. 3. Regression relationships between the measured and predicted values to demonstrate the goodness of fit of the results.

3.4. Model performance (validation) evaluation

An important problem is whether results of the regression analysis on the sample can be extended to the population the sample has been chosen from. If this happens, then we say that the model has a good fit and we refer to this question as a goodness-of-fit analysis, performance analysis or model validation analysis for the model. Application of modelling techniques without subsequent performance analysis of the obtained models can result in poorly fitting results that inaccurately predict outcomes on new subjects. Simply, building a predictive model was not our motive. But, creating and selecting a model which gives high accuracy on out of sample data. Hence, it is crucial to check accuracy of the model prior to computing predicted values. In order to assess the developed pedo-transfer function model performance, the test data points were used to predict soil OC and the predicted values were plotted against observed values. The scatter plot of the observed versus predicted values are shown in Fig. 3. As you can see from Fig. 3 that the plot approximates a straight line ($R^2 = 0.81$) with the line of equality (1.0:1.0), and an angle close to 45 (one to one line), which indicates the high accuracy of the developed pedo-transfer function model for the estimation of soil OC. These observations suggest further that soil texture is a powerful predictor variable on indirect estimation of the contents of OC in soils.

4. Conclusions

Soil OC contents differ significantly across soil types when at a defined ecological setting. Multiple regression pedo-transfer function based on soil texture was used to predict soil OC contents in coastal plains maize croplands of Tanzania. Soil textural parameters of sand, clay and silt in all combinations were found powerful predictors ($R^2 = 0.82, p < 0.001$) of OC contents in soils. Soil texture is therefore a strong influencing factor for the variability of soil OC contents in soils. It is concluded further that, the use of pedo-transfer function for predicting soil OC based on soil texture could provide an easy, economic and brief methodology for estimation OC contents in soils. It is recommended to carry out more pedo-transfer function studies for predicting not only soil OC but also other soil properties based on soil texture in other agro-ecosystems of Tanzania.

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